CARBON STOCK ASSESSMENT IN PINE FOREST OF KEDUNG BULUS SUB-WATERSHED (GOMBONG DISTRICT) USING REMOTE SENSING AND FOREST INVENTORY DATA

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ABSTRACT

Carbon stock in tree biomass can be quantified directly by cutting and weighing trees. It is assumed that 50% of the dry weight of biomass consists of carbon. This direct measurement is the most accurate method, however for large areas it is considered time consuming and costly. Remote sensing has been proven to be an important tool for mapping and monitoring carbon stock from landscape to global scale in order to support forest management and policy practices. The study aimed to (1) develop regression models for estimating carbon stock of pine forests using field measurement and remotely sensed data; and (2) quantify soil carbon stock under pine forests using field measurement. The study was conducted in Kedung Bulus sub-watershed, Gombong - Central Java. The derived data from *Satellite Probatoire d'Observation de la Terre* (SPOT) included spectral band 1, 2, 3, and 4, Normalized Differences Vegetation Index (NDVI), and Principle Component Analysis (PCA) images. These data were integrated with field measurement to develop models. Soil samples were collected by augering for every 20 cm until a depth of 100 cm. The potential of remote sensing to estimate carbon stock was shown by the strong correlation between multiple bands of SPOT (band 2 , 3; band 1, 2, 3; band 1, 3, 4; and band 1, 2, 3, 4) and carbon stock with $r = 0.76$, PCA (PC1, PC2, PC3) and carbon stock with $r = 0.73$. The role of pine forest to reduce CO_2 in the atmosphere was demonstrated by the amount of carbon in the tree and the soil. Carbon stock in the tree biomass varied from 26 to 206 Mg C ha^{-1} and in the soil under pine forest ranged from 85 to 194 Mg C ha^{-1}.

Keywords: Remote sensing, carbon stock, field measurement

I. INTRODUCTION

Carbon stock assessment in a forest ecosystem is necessary for many applications, from conservation of land productivity to emission mitigation of CO_2 purposes. Carbon stock in tree biomass can be assessed using a destructive method or non-destructive methods, such as allometric equations or models based on remote sensing. Direct measurement through destructive sampling can be conducted by felling and weighing tree biomass and assuming that 50% of the dry biomass composed by carbon organic (Intergovernmental Panel on Climate Change/ IPCC, 2003).

Direct measurement of carbon stock in tree biomass is considered impractical for large areas (Gibbs *et al*., 2004). In this regard, remote sensing can be used to estimate tree biomass for landscape or broader levels. Remotely sensed data provide continuos information, cover large area, and objective data (Foody *et al*., 2003; Rosenqvist *et al*., 2003). A common method to assess above-ground biomass (AGB) or carbon stock in tree biomass using remote sensing is by developing a regression model between extracted values from a remote sensing image and AGB or tree parameters from field measurement. The developed model, then used to predict AGB for other trees having similar characteristics to those of the trees used to develop the regression model. The extracted values are considered as independent variable and can be extracted from a

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single band, vegetation index, or image transformation.

Steininger (2000) reported that spectral band 5 (middle infrared spectrum) of Landsat TM had a strong correlation with above-ground biomass in Brazilian forests. While Tangki and Chappell (2008) observed that radiance of band 4 (near infrared) or band 5 of Landsat TM image can be used to estimate above-ground biomass in *Dipterocarp* forest. Simple and advanced vegetation indices have been developed to predict carbon stock in tree biomass. A simple vegetation index such as normalized difference vegetation index (NDVI) is frequently applied to estimate forest stand parameters or AGB.

In addition to vegetation indices, a transformation technique such as Principal Component Analysis (PCA) is applied to estimate tree biomass. The purpose of this transformation is to compress all of the information contained in an original *n*-band data set into fewer than *n* "new bands" (Lillesand *et al.*, 2004). The new bands are then used instead of the original data. Principal component image data values are simply linear combinations of the original data values multiplied by the appropriate transformation coefficients. These coefficients are statistical quantities known as *eigenvectors* or *principal components* which are derived from the variance/covariance matrix of the original image data (Lillesand *et al.*, 2004). In other words, principal component image is a linear combination of the original data and the eigenvector on a pixel-by-pixel basis throughout the image. Image transformation using PCA was successfully applied by Lu *et al.* (2004) for biomass estimation in Brazilian forest. It was observed that PC1 had strong correlation with above-ground biomass (Lu *et al.*, 2004).

Although all the studies mentioned above reported that independent variables derived from remotely sensed data had strong correlation with above-ground biomass, however, the models were not validated. Transferability of the models to other study areas is uncertain. Therefore, in this study we developed regression models followed by validation using independent data set.

Besides quantifying carbon stock in tree biomass, assessment on soil organic carbon is necessary because soil can also be used as a carbon sinks. In addition, soil is an important source of nutrient and as media for crops and forests growth (Harrison *et al.*, 2011). Surface and sub-surface soils are essential to store organic carbon; however, most study examined organic carbon only in surface horizon. The potential of sub-surface soil to sequester carbon was found by Lorenz *et al.* (2011). They reported that soil under coniferous forest can store organic carbon around 76%.

The purpose of this study are (1) to develop regression models for estimating carbon stock of pine forests using field measurement and remotely sensed data; and (2) to quantify soil carbon stock under pine forests using field measurement. In this study, we applied a single band, NDVI, and PCA to estimate carbon stock in tree biomass. In addition, multi bands combination are also used in order to improve the accuracy of carbon stock estimation.

II. MATERIAL AND METHOD

A. Study Area and Ground Data Collection

The study was conducted in Kedung Bulus sub-watershed in Gombong, Central Java. The location lies between 336000 mE - 345000 mE and 9162500 mS - 9170000 mS. The forest is dominated by pine (*Pinus merkusii*) with various ages, from 4 to 37 years. Soil in the study area are association of Distropets, Tropudults, and Troportents. Rainfall recorded in Somagede climate station from 2009 to 2012 showed that the mean annual rainfall was 3202 mm yr^{-1}, and the mean monthly rainfall ranged from 7 to 628 mm $month^{-1}$. Topographic is from undulating to rolling with gentle to very steep slopes Figure 1 shows location of the study area.

A field measurement was conducted to collect the necessary data. A purposive sampling regarding to stand age was applied to allocate 31 sample plots. The size of the plot was 20 by 20 m. The DBH of all of the trees within each plot were measured. Twenty one plots were used for developing regression models and the rest were for validation. The diameter range and the number of trees within each plot are presented in Table 1.

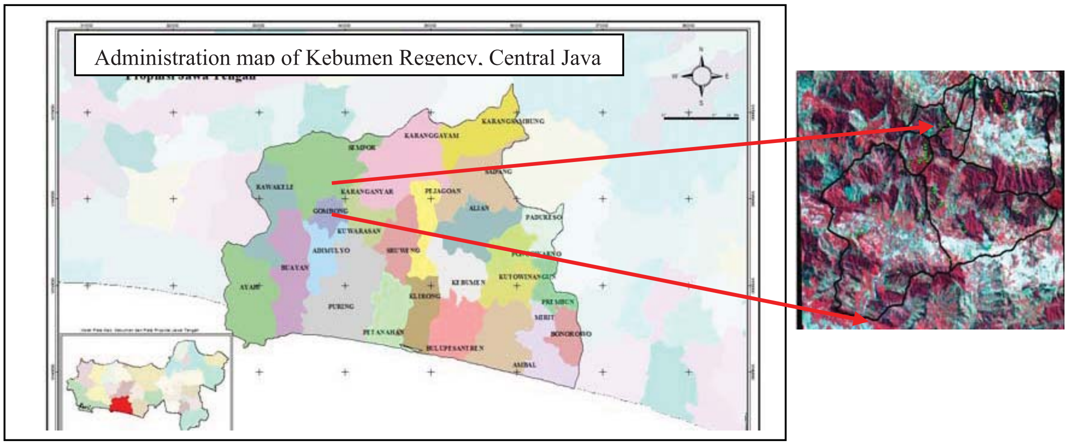


Figure 1. Location of the study area on SPOT 4 (black line is the boundary of Kedung Bulus sub-watershed)

Table 1. Characteristics of the trees within each plot for training and validation of the models

	No	Age (Year)	Diameter (cm)			No of tree per plot
			Minimum	Maximum	Average	
Training plot	1	34	21.3	47.8	37.4	19
	2	34	23.6	47.4	35.2	15
	3	4	4.1	19.7	10.0	47
	4	34	25.5	47.5	40.1	14
	5	36	16.2	47.8	32.3	18
	6	11	5.4	31.2	15.7	36
	7	21	17.2	37.9	28.2	22
	8	14	8.6	33.7	23.6	28
	9	25	21.8	39.2	30.3	20
	10	11	8.0	29.6	20.7	28
	11	26	25.5	39.5	35.1	14
	12	22	24.5	43.0	31.9	23
	13	34	25.8	45.2	34.4	15
	14	26	18.2	38.2	27.4	20
	15	34	30.9	58.9	41.5	11
	16	32	18.2	42.4	32.5	29
	17	17	9.6	28.7	22.0	22
	18	37	15.9	47.8	32.5	15
	19	24	14.3	37.6	25.9	31
	20	24	13.1	40.4	24.7	31
	21	10	18.8	29.0	23.6	16
Validation plot	1	25	27.1	61.8	37.1	19
	2	19	12.4	41.7	24.8	29
	3	34	27.4	47.5	37.2	15
	4	34	30.6	57.3	41.5	14
	5	26	14.3	34.1	24.6	23
	6	17	11.1	35.0	23.0	29
	7	14	10.2	35.4	25.3	19
	8	37	29.6	47.8	38.0	15
	9	14	22.5	28.7	22.5	23
	10	10	9.6	28.3	20.0	35

An allometric equation for pine forest (IPCC, 2003) was used to convert the DBH data from field measurement into above ground biomass. This equation was constructed from 137 trees with DBH ranged from 0.6 to 56 cm, the R^2 of the equation was 0.98 (IPCC, 2003). The formula is:

$$Y = 0.887 + [(10486 * (DBH)^{2.84})/((DBH^{2.84}) + 376907)] \quad (1)$$

Where:
Y = above-ground tree biomass dry in matter (kg)
DBH= diameter at breast height (cm)

The above-ground biomass resulted from the allometric equation was converted to carbon stock by assuming that 50 % of the biomass consisted of carbon (IPCC, 2003).

Soil samples were collected by augering for every 20 cm depth until 100 cm or less than 100 cm when parent material was found. The samples were undertaken from 8 selected plots where the forest inventories were conducted. The soil organic matter was analyzed using Walkley and Black method in the laboratory.

B. Image Processing and Data Analysis

A SPOT 4 image acquired in May 13 2008, path/row 291/365, was geo-rectified to the Universal Transverse Mercator (UTM) coordinate system with datum WGS 1984 and zone 49 South. This image was used to generate independent variables consisted of spectral band 1 (green), band 2 (red), band 3 (near infrared), band 4 (middle infrared), NDVI and PCA.

Two types of NDVI were generated using the following formula:

$$NDVI23 = (b2-b3)/(b2+b3) \quad (2)$$
$$NDVI24 = (b2-b4)/(b2+b4) \quad (3)$$

Where:
NDVI23 is normalized difference vegetation index derived from band 2 and band 3
NDVI24 is normalized difference vegetation index derived from band 2 and band 4

For the PCA, Figure 2 shows that data along the direction of the first component (axis I) have a greater variance or dynamic range than data plotted against either of the original axes (band A and B).The data along the second principal component direction have less variance. This is a characteristic for all the principal component images. In general, the first principal component (PC1) includes the largest percentage of the total scene succeeding components images (PC2, Pc3, ….PCn) in which each contains a decreasing percentage of scene variance.

To reduce error from GPS reading and geo-referencing, the independent variables were the mean of the extracted values from 3 x 3 pixels (Austin *et al.*, 2003; Lucas *et al.*, 2006).

Prior developing the regression models, the AGB data were tested for the normality (Figure 3). Simple and multiple regression models were developed to examine the correlations between dependent variable (carbon stock) and independent variable (spectral band of SPOT 4 and PCA) using the training data. Every model was cross validated using an independent data set (n=10).

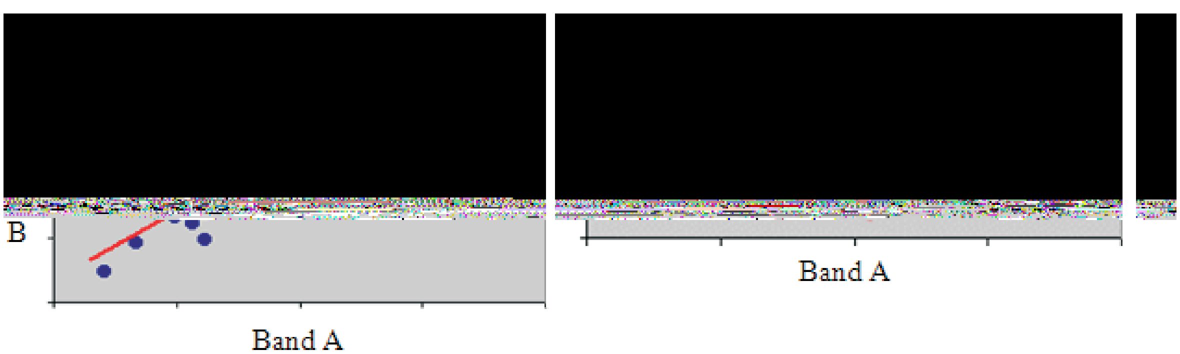


Figure 2. Rotated coordinates axes used in principal component analyses
(Source: Lillesand *et al.*, 2004)

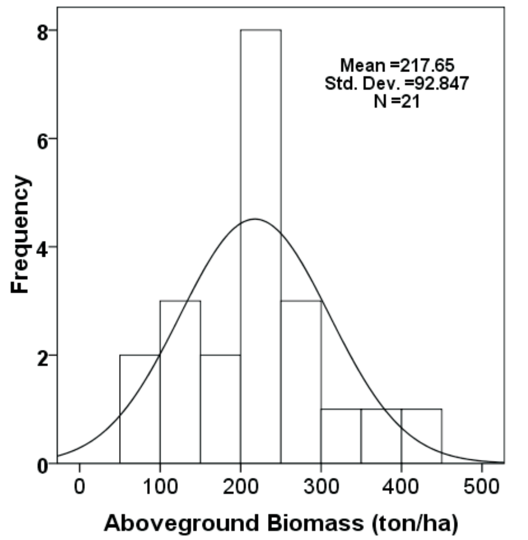


Figure 3. Normality test for the training data (n=21)

III. RESULT AND DISCUSSION

A. Aboveground Carbon Stock Estimation Using Remotely Sensed Data and Field Measurements

Based on the computation using the IPCC (2003)'s allometric equation, the estimated aboveground carbon stocks in the plot vary from 26 to 206 Mg C ha^{-1} (Table 2).

The estimated carbon stocks from plot measurements were assumed to be the measured values and then these were correlated with extracted values of the SPOT image. Table 3 presents regression models between independent (remotely sensed data) and dependent (carbon stock in tree biomass) variables. For a single band, near infrared band (b3) of SPOT 4 shows the highest correlation with carbon stock in tree biomass, while PC3 and PC2 do not correlate with carbon in tree biomass. In the near infrared spectrum region, vegetation provides the strongest reflectance that can be captured by the sensor. Chlorophyll content reflects most of the near infrared spectrum. Moreover, chlorophyll content of vegetation represents the canopy volume. This phenomenon is in agreement with research conducted by Tangki and Campell (2008) who found a strong relationship between above-ground biomass with near infrared band of Landsat-5 TM.

Multiple bands combination tends to slightly improve correlation between the remotely sensed data with the carbon stock in tree biomass. Multiple bands combinations involving the near infrared (e.g. b1,3; b2,3; b1,2,3; b2,3,4; and b1,2,3,4) provide higher correlation compared to the other combinations. Similar results are obtained by Basuki *et al*. (2012). Regression

Table 2. The aboveground C-stock estimated using the IPCC (2003)'s allometric equation in the 21 points for modeling

Plot no.	Aboveground C-stock (Mg C ha^{-1})	Plot no.	Aboveground C-stock (Mg C ha^{-1})	Plot no.	Aboveground C-stock (Mg C ha^{-1})
1	164.7	8	93.1	15	118.1
2	114.2	9	116.6	16	189.6
3	27.6	10	70.5	17	63.5
4	140.0	11	104.0	18	206.4
5	120.5	12	140.5	19	127.5
6	25.9	13	109.0	20	114.3
7	104.7	14	83.2	21	51.2

Table 3. Pearson correlation between carbon stock in tree biomass and a single band or multiple bands combinations of SPOT 4 or PCA using 21 training data

No	Regression model	Pearson correlation
1	Y = 259.81 – 1.47*b1	0.38
2	Y = 274.22 – 5.52*b2	0.69
3	Y = 534.27 – 8.62*b3	0.73
4	Y = 252.20 – 2.07*b4	0.68
5	Y =325.00 – 0.62*b1 – 5.08*b2	0.71
6	Y = 542.20 – 0.21*b1 – 8.33*b3	0.75
7	Y = 304.28 – 0.62*b1 – 1.90*b4	0.70
8	Y = 782.27 + 6.21*b2 – 17.41*b3	0.76
9	Y = 274.02 – 3.21*b2 – 1.00*b4	0.71
10	Y = 512.82 – 7.88*b3 – 0.21*b4	0.74
11	Y = 807.36 + 0.19*b1 + 7.02*b2 -18.80*b3	0.76
12	Y = 319.82 -0.56*b1 -3.03*b2 -0.90*b4	0.72
13	Y = 758.24 + 6.27*b1 -16.59*b3 – 0.27*b4	0.76
14	Y = 783.13 + 0.17*b1 + 6.98*b2 -17.90*b3 – 0.23*b4	0.76
15	Y = -39.80 – 594.56*NDVI23	0.64
16	Y = 164.84 + 143.00*NDVI24	0.14
17	Y = 332.73 – 1.89*PC1	0.71
18	Y = 103.51 – 0.09*PC2	0.02
19	Y = 112.36 – 0.15*PC3	0.01
20	Y = 371.29 – 1.97*PC1 – 0.51*PC2 – 2.48*PC3	0.73

Remarks:
Y = Predicted carbon stock in above-ground tree biomass
b1, b2, b3, b4 = retrieval values of b1, b2, b3, and b4 of SPOT imagery
NDVI = Normalized Difference Vegetation Index
PC = Principle Component

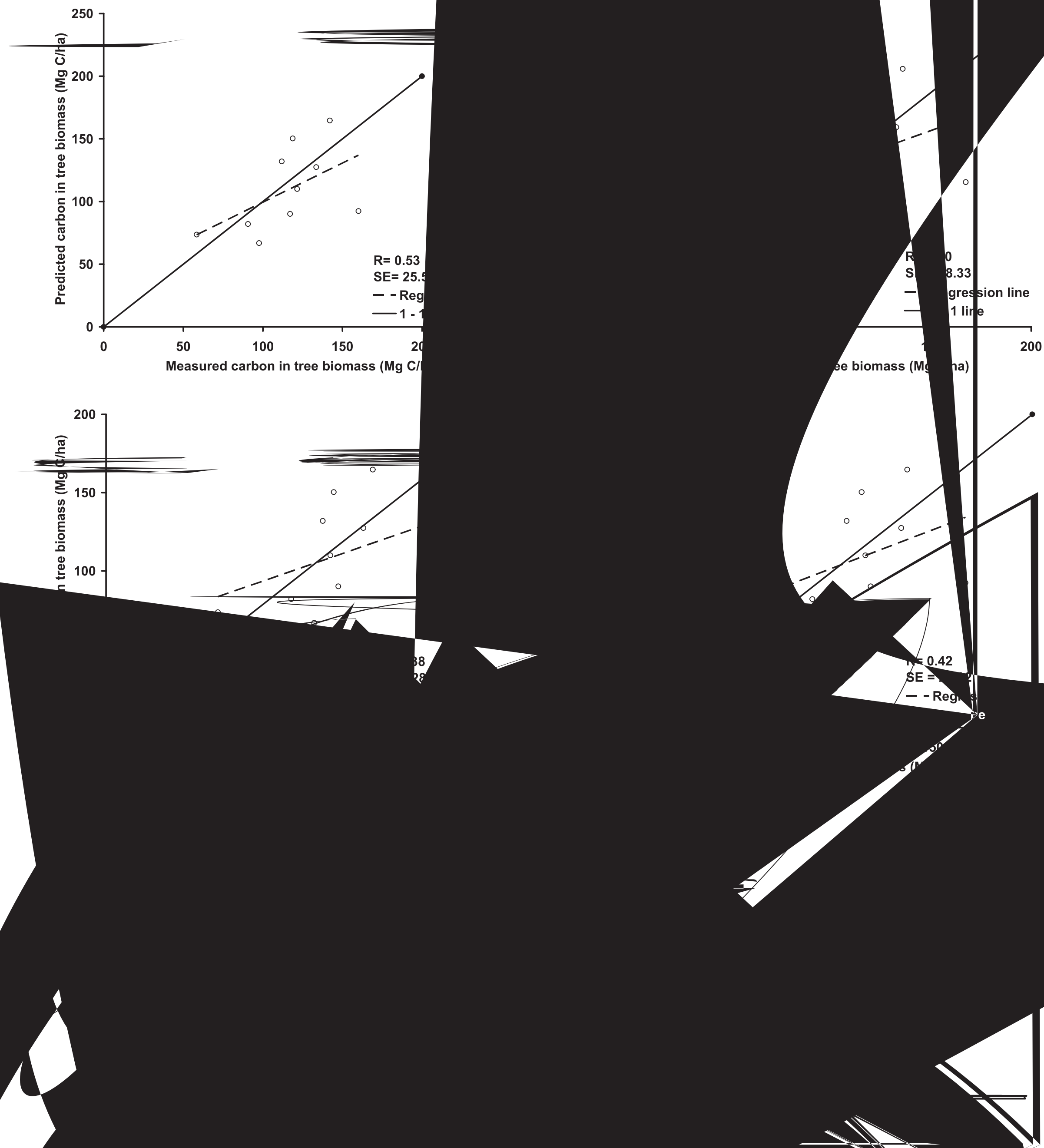
models using multi bands combinations increased the coefficient correlation of the model because every band complements to each other.

The vegetation indices (NDVI) derived from red and near infrared bands provide higher correlation with carbon stock than NDVI derived from red and middle infrared bands (Table 3). A possible explanation for this result is that in the infrared region vegetation has higher reflectance than in the middle red region. As expected, PC1 provides the highest correlation with carbon stock in tree biomass compared to PC2 and PC3. This condition is because the data have been compressed and presented in PC1. A multiple combination of PC 1, 2, and 3 does not significantly improve the Pearson correlation (Table 3) because the PC 2 and 3 do not have correlation with the carbon stock in tree biomass.. The highest correlation between PC1 and AGB compared to PC2, PC3 and AGB is also found by Lu *et al*. (2004) in Amazonian forest in Brazil.

B. Validation of The Regression Models

Regression models having Pearson correlation 0.75 and the model based on PC 1, 2, and 3 were applied to the independent data set for validation. Figure 4 shows the measured and the predicted of carbon stock in the tree biomass. The 1 - 1 line is used to examine whether predicted values are higher or lower than the measured carbon stock. Although Pearson correlation of the regression model based on PC1, 2, and 3 is slightly lower than that of the multiple bands combinations using band 3 (Table 3). However, validation using an independent data set suggests that the model based on the PC1, 2, and 3 is more stable. This is shown by the Pearson correlation (r = 0.63) between the measured and the predicted carbon as presented in Figure 4, it means that this model more applicable than the others.

The correlation between the carbon stock and the independent variables (spectral band of SPOT imagery, NDVI, and PC) may be improved by additional sample plots and topographic correction. In a rugged terrain, a topographic correction is needed because a high variation in the reflectance response for similar vegetation condition (Riao *et al*., 2003). However, Tokola *et al*. (2001) observed that a simple non-Lambertian method could not be applied to normalize topographic effects and significantly improve the accuracy of AGB estimation.



... in t... biomas... (Mg C/ha) using different ... ependent da...). The independent variables ... 1,2,3; b2,3,4; b1,... PC1,2,3

C. Soi...

C... ks in the soil under Pine forest var... fr... the others (Table 4). The amount ... ange from 85 to 194 Mg C ha^{-1}. ... lower than SOC found by ... et ... (2010) under pine plantation in ... n SOC under pine forest at 25 cm dep... ha^{-1} (Loaiza *et al*., 2010), while in the ... from 18 to 47 Mg C ha^{-1}

Table 4. Soil organic carbon

No	The age of pine stand (year)	Soil depth (cm)	Soil organic carbon (Mg C ha^{-1})
1.	34	0 – 20 cm	20.50
		20 – 40 cm	18.50
		40 – 60 cm	18.50
		60 – 80 cm	12.75
		80 – 100 cm	14.75
		Total	85.00
2.	34	0 – 20 cm	24.75
		20 – 40 cm	34.25
		40 – 60 cm	38.75
		60 – 80 cm	26.00
		80 – 100 cm	26.00
		Total	149.75
3.	34	0 – 20 cm	30.00
		20 – 40 cm	43.00
		40 – 60 cm	47.25
		60 – 80 cm	26.00
		80 – 100 cm	47.50
		Total	193.75
4.	36	0 – 20 cm	23.75
		20 – 40 cm	23.25
		40 – 60 cm	28.00
		60 – 80 cm	19.25
		80 – 100 cm	19.50
		Total	113.75
5.	9	0 – 20 cm	18.00
		20 – 40 cm	24.00
		40 – 60 cm	21.75
		60 – 80 cm	26.25
		80 – 100 cm	17.50
		Total	107.50
6.	21	0 – 20 cm	39.50
		20 – 40 cm	34.25
		40 – 60 cm	23.75
		60 – 80 cm	30.00
		80 – 100 cm	30.00
		Total	157.50
7.	14	0 – 20 cm	47.00
		20 – 40 cm	25.50
		40 – 60 cm	21.50
		60 – 80 cm	17.25
		80 – 100 cm	10.75
		Total	122.00
8.	25	0 – 20 cm	34.75
		20 – 40 cm	34.25
		40 – 60 cm	27.75
		60 – 80 cm	30.00
		Total	126.75

Table 5. Ratio carbon stock in soil and tree biomass

No.	The age of pine stand (year)	Carbon stock in aboveground tree biomass (Mg C ha^{-1})	Soil organic carbon at 100 cm depth (Mg C ha^{-1})	Ratio of soil carbon stock to above-ground biomass carbon (%)
1.	34	164.70	85.00	52
2.	34	114.22	149.75	131
3.	34	139.95	193.75	138
4.	36	120.48	113.75	94
5.	9	25.91	107.50	415
6.	21	104.68	157.50	150
7.	14	93.14	122.00	131
8.	25	116.14	126.75	109

Our study showed that soil organic carbon under old stand (34-36 years old) was not always higher than that of young one. Among the plots, the highest and the lowest soil carbon was found in 34 years pine forest (Table 4), this phenomenon could be caused by differences in biophysical conditions of the plots. Regarding to differences of soil organic carbon from one plot to the other could be caused by differences in soil texture, density of the trees, and topographic condition (Lal, 2005).

The potential of soil to reduce CO_2 from the atmosphere can be seen by the ratio of carbon stock in tree biomass and in the soil which are more than 100%. This means the SOC higher than organic carbon in tree biomass(Table 5). As comparison, Loaiza *et al.* (2010) found that the ratio of SOC at 50 cm depth to carbon stock in tree biomass was 169% in tropical pine forest in Brazil. In addition, Allewell *et al.* (2009) stated that soil stores twice as much carbon as the atmosphere. Therefore maintaining soil productivity through conservation practices is essential to store organic carbon in soil since it is considered a slow renewable source (Harrison *et al.*, 2011) and stabilizing organic carbon in soil horizons is essential to mitigate human-induced climate change (Lorenz *et al.*, 2011).

IV. CONCLUSION

The study demonstrates the potential of remote sensing method to assess carbon stock of tree biomass. To achieve a higher accuracy of the assessment, more sample plots which represent various ages of the plantation, various amounts of biomass and biophysical conditions are needed. The study also highlights the potential role of forest soil for CO_2 mitigation. At a depth 100 cm, forest soil can store more carbon than that of forest biomass.

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